EFFECTIVE INSPECTOR FOR DETECTING FOREIGN SUBSTANCES IN BOTTLES WITH INHOMOGENEOUS STRUCTURES

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ABSTRACT. *In order to solve the problem of high costs and low efficiency caused by manual inspection, an automatic inspector for foreign substances in bottles with inhomogeneous structures based on machine vision technology is proposed in this paper. First, we extract the region of interest based on meanshift segmentation and align the images by registration and rectification. Then an adaptive image variation detection method is established to locate the potential foreign substances. To avoid the brightness disturbances caused by inhomogeneous structures on the bottles, an occurrence probability image which models the probability of each changed pixel to be true foreign substance is learned and candidate foreign substances are obtained by taking account of both the probability distribution and brightness variation. Finally, SVM classifier is applied to further identifying foreign substances based on their appearance features. Experiments show that this inspection algorithm has satisfactory detection accuracy and can greatly inhibit false detection caused by inhomogeneous structures.*
Keywords: Machine vision, Probability distribution, Foreign substances detection, Inhomogeneous structure

1. **Introduction.** Foreign substances detection in bottling industry usually relies on manual inspection. As the development of machine vision techniques, automatic detection is possible, with more efficiency and lower cost. Common methods of tracking moving objects include frame difference (FD), optical flow algorithm and background subtraction. The standard optical flow method has poor real-time performance because of its high complexity [1]. The background subtraction method shows limited success because the background is not constant due to the appearance and location difference between different bottles caused by different camera triggering time [2]. Besides, for edible oil bottles there are usually various inhomogeneous structures on the bottle's surface as shown in Figure 1, which will easily cause brightness variations that may be confused with true foreign substances. As the brightness of inhomogeneous structures varies from image to image, it is difficult for the background subtraction method to eliminate them in all images.

The FD method is most widely used in this field to track foreign substances from image sequences in which the changed part between different images is extracted to distinguish
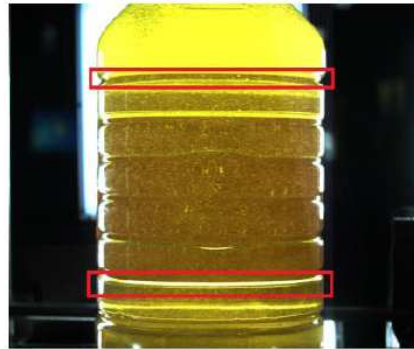
FIGURE 1. Inhomogeneous structures on the bottle's surface

the moving objects and the background [3,4]; however, a special hardware platform should be established for this method which rotates bottles spirally, stops abruptly, collects images and then processes images [5,6]. A two-stage frame difference method based on sub-pixel registration of image sequences was reported in [7], to extract the trajectory of small targets while eliminating the interference from complex background. A binocular particle inspection machine was specified in [8]. By using binocular algorithm and image difference based stereo correspondence, it can overcome the problem of shallow depth of field of the camera and interference problem caused by the dynamic background. However, FD methods are mainly suitable for beer bottles and ampule bottles which are small in size because the detection performance of FD method suffers from the speed of the moving object and interval between frames. For large bottles such as the edible oil bottles, it is not realistic to build a rotating-stopping platform for them. Therefore, traditional image difference methods cannot be applied.

In our previous study, an impurity detection algorithm for bottles filled with edible oil using a single image is proposed in [9], in which impurities are detected using integral images. This method shows good performance on detection of dark or bright foreign substances, but it cannot tell the difference between a dark/bright impurity region and a dark/bright pattern on the surface of the bottle. As a result, we need a more robust algorithm which can handle the background variation.

To solve these problems, an effective inspector for foreign substances in edible oil bottles with inhomogeneous structures based on machine vision is presented in this paper. Different from traditional frame difference methods which need to set up a special hardware platform, this system only needs a simple image capture device. An adaptive image variation detection method is constructed to find out the candidate foreign substances using single frame, and an occurrence probability image which models the probability of each changed pixel to be true foreign substance is constructed to eliminate false detection caused by inhomogeneous structures. Experiments show that this inspection algorithm can satisfy the demands of bottling production line and have high detection accuracy.

The paper is organized as the following. Firstly, the hardware structure of the system and the framework of the algorithm are introduced in Section 2. Secondly, the pre-processing steps are described in Section 3, including ROI location and images alignment. Thirdly, the detection algorithm is presented in detail in Section 4, including adaptive image variation detection, structure related occurrence probability image modeling, candidate objects detection and foreign substances identification. Finally, the experiment and analysis are shown in Section 5, and conclusions are made in Section 6.

2. **System Design.** The inspector presented consists of several hardware devices to capture and process the acquired images, including conveyors, light source, color cameras, industrial control computer and control board. The inspector uses a flat back light source
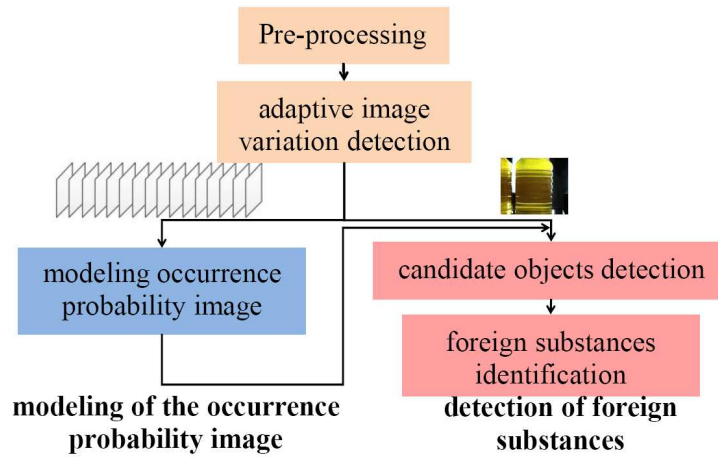
FIGURE 2. The framework of the proposed algorithm

to illuminate the entire bottle. While oil bottles are transmitted to the detection area, optical triggers transmit signals to the cameras to capture the images of bottles in the field of view. After that, the industrial control computer processes the images and sends out corresponding instructions such as kicking instruction for defected bottles. A user operation interface is also developed by which the user can set system parameters such as detection ROI and judgment rules.

The complete framework of the proposed algorithm is shown in Figure 2, which mainly contains two modules: modeling of the occurrence probability image and detection of foreign substances. The two modules share a same pre-processing step which includes ROI location and image alignment, and a same adaptive image variation detection step which is used to locate the potential foreign substances, as well as the inhomogeneous structures. In the modeling step, a series of sample images are learned to model the occurrence probability image. In the detection step, candidate foreign substances are obtained by taking account of both the probability distribution and brightness variation, and then to further remove noise interference, SVM classifier is utilized.

3. Pre-processing Step.

3.1. **ROI location.** As oil bottles are transmitted horizontally on the conveyors, the varying space interval of consecutive bottles and the trigger time delay may lead to a horizontal offset of bottles on the captured images. To locate the bottles, most researches use lateral scanning method, by which they scan an image horizontally and obtain the bottle's left and right edges, and then region of interest (ROI) which indicates the location of the entire bottle can be extracted based on the known shape of the bottle [10]. This method cannot locate the bottle when there are two bottles in the same images as shown in Figure 3(a).

Considering the color difference between the oil and the background, we propose an ROI extraction method by using the mean shift segmentation algorithm [11,12]. Pixels in the images are categorized into different areas with different sizes as shown in Figure 3(b). Then by selecting the areas with a specified size and vertical offset, the ROI of the bottle can be extracted. As bottles may reflect lights and bubbles in the oil may refract lights, there might be cavities and noise in the extracted ROI, so morphology processing is used to get the whole correct ROI of the bottle.

3.2. **Images alignment.** To eliminate the interference of inhomogeneous structures, all the bottles in the images should be aligned using image registration and image rectification. Considering that the offset mainly occurs on the horizontal direction, we first
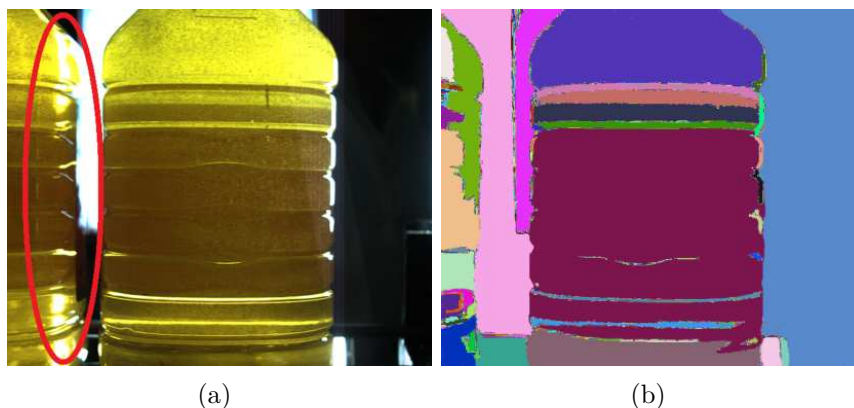
FIGURE 3. (a) Interference on the background of the bottles, (b) images after using mean shift segmentation algorithm

convert the ROI image to gray image $R(i,j)$, and define the horizontal medial axis of the bottle as

$$X_{ROI} = \frac{1}{N_{ROI}} \sum_{n=1}^{N_{ROI}} r_n, \quad \text{if } R(i,j) \neq 0, \tag{1}$$

where N_{ROI} is the number of pixels with nonzero gray value, and r_n is the horizontal coordinates of these pixels. Then we can get offset O_{ROI} easily and rectify the image as

$$R'(i,j) = R(i, j + O_{ROI}). \tag{2}$$

4. **Detection.**

4.1. **Adaptive image variation detection.** The foreign substances in the oil bottle and the inhomogeneous structures on the bottle will block the light illumination; as a result, they both appear as the darker areas in the image. To locate the potential foreign substances, as well as the inhomogeneous structures, we propose a simple but effective adaptive image variation detection method, in which we first obtain a smoothing image of the bottle and then remove it from the original image to indicate the variation areas.

We set the size of the smoothing window as $(2a + 1) \times (2a + 1)$ and define the mean energy values of the window as gray value of the central pixels in the smoothed image. Such mean energy value takes the form as

$$\mu(i,j) = \frac{1}{n_W} \sum_{i'=i-a}^{i+a} \sum_{j'=j-a}^{j+a} R'(i',j'). \tag{3}$$

n_W is the number of pixels in the window whose gray values are not zero. Note that to ensure that inhomogeneous structures can be smoothed, the window size should be wider than that of the inhomogeneous structure. As variation areas are darker in the image, we can subtract the original image from the smoothed image to get the variation areas. The difference image is defined as

$$D(i,j) = Max(0, \mu(i,j) - R'(i,j)). \tag{4}$$

4.2. **Structure related occurrence probability model.** In the bottling production line, the image brightness distribution varies from bottles to bottles. This is mainly caused by the bubbles in the bottles which are generated during the production step named injection of nitrogen. The quantities and locations of bubbles are random and will cause uneven brightness in the images. Different from the brightness distribution, however, the structural information shows good stability, which inspired us to modeling an occurrence probability model to locate the candidate foreign substances.

First we capture the structural information by highlighting the inhomogeneous structure parts via threshold segmentation as

$$G(i,j) = \begin{cases} 255 & D(i,j) \geq T \\ 0 & \text{else} \end{cases}, \tag{5}$$

where T is the threshold value.

Then we model the occurrence probability image, where each pixel's value represents the probability of whether or not the corresponding pixel in oil image belongs to foreign substances. The value of 1 represents the maximum probability, and the smaller value indicates smaller possibility. The initial value of the occurrence probability image is defined as 1, and the learning function to model the occurrence probability image takes the form as

$$P'(i,j) = \begin{cases} R_{learning} * P(i,j), & G(i,j) = 255 \\ 1/R_{learning} * P(i,j), & G(i,j) = 0 \end{cases} \tag{6}$$

$P(i,j)$ is the present occurrence probability image and $P'(i,j)$ is the updated one, whose maximum of gray value is no more than 1. $R_{learning}$ is the learning rate ($0 < R_{learning} < 1$). As shown in Figure 4, when $G(i,j) = 0$ or $G(i,j) = 255$, the learning function grows positively or negatively, respectively. Finally, by learning with a certain number of samples, usually from 100 to 300, a stable occurrence probability image can be got. The computation is simple with low hardware requirements, which can meet the real-time and practical demands in bottling industry.
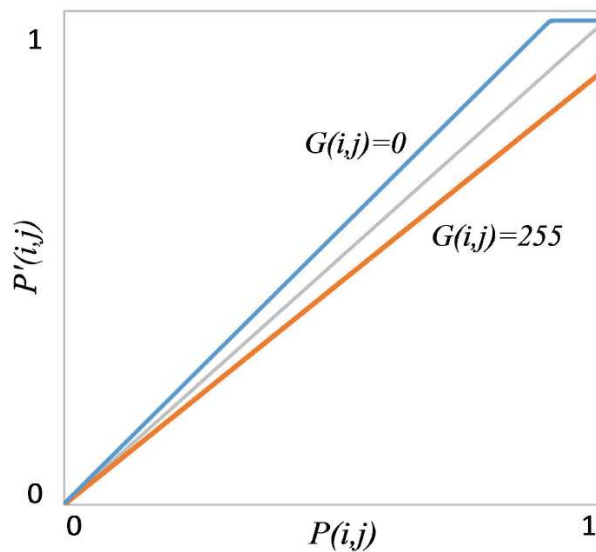

FIGURE 4. Learning function of modeling occurrence probability image

While we learn about the inhomogeneous structures information, the foreign substances in the bottle or burst ambient light changes will also influence the modeling process. To examine the performance of the learning method under those interferences, we select 200 images and focus on a fixed pixel $G(i_0, j_0)$ in the image sequences. The corresponding $P(i_0, j_0)$ is multiplied by 255 for visualization. The gray value variation tendency is shown in Figure 5.

From Figure 5 we can see that most gray values of $G(i_0, j_0)$ in image sequences are 0, while there might be some burst interference to make the value become 255. This method shows a good ability of interference suppression and the final value is approximated to 0, which is consistent with the fact. Besides, learning speed is quite fast. It is gradually stabilizing after learning about 100 samples.
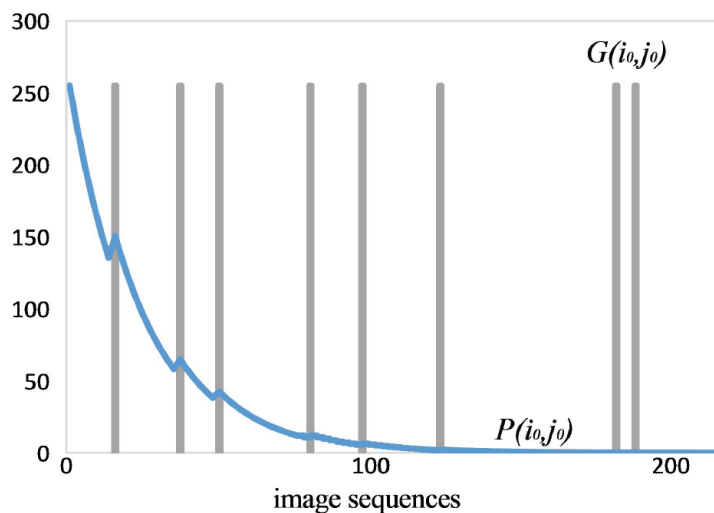
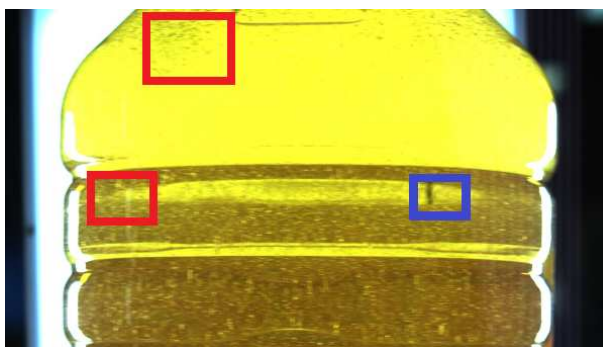FIGURE 5. Variation tendency of occurrence probability image

FIGURE 6. Foreign substances and interference of bubbles and irregular structures

4.3. **Candidate objects detection.** During the online real-time detection step, adaptive image variation detection is first used to obtain brightness variation in the bottle image, then candidate foreign substances are obtained by taking account of both the occurrence probability and brightness variation. Inhomogeneous structure parts can be removed by multiplying $D(i, j)$ with $P(i, j)$ and using simple threshold segmentation.

$$C(i, j) = \begin{cases} 255 & D(i, j) * P(i, j) \geq T' \\ 0 & \text{else} \end{cases} \tag{7}$$

$C(i, j)$ is the image with candidate objects and T' is the threshold value.

4.4. **Foreign substances identification.** There might be some interference in candidate objects, such as irregular structures and bubbles that would not exist in every bottle and cannot be removed by occurrence probability image, as shown in Figure 6. Therefore, a foreign substances identification algorithm based on SVM classifier [13] is used. We choose the following features of each candidate object in Table 1 as the input vectors to train SVM and realize classification.

5. **Experiments and Analysis.** The inspector designed adopts SVS 5 mega-pixel color camera and Ricoh 16mm lens, as well as a flat oblong LED light source, and runs on a Linux operation system.

Before online detection, an occurrence probability image is learned with about 200-300 samples to model occurrence probability image. We first apply ROI extraction and image alignment to pre-processing these samples, as shown in Figure 7(a). Then adaptive image variation detection is adopted to obtain the inhomogeneous structures, as shown

TABLE 1. Feature extraction and feature selection

Gray mean value	$\mu = \frac{1}{N_C} \sum_{n=1}^{N_C} C_n.$	C_n is the gray value of the nth pixel in the candidate object, and N_C is the pixel number of this candidate object.
Contrast value	$C = \frac{1}{M} \sum_{i=1}^{M} \sigma_i.$	$\sigma_1, \sigma_2, \sigma_3, \ldots, \sigma_M$ are variance of each edge pixel's $7*7$ neighborhood, and M is the number of edge pixels.
Shape	$k_B = \frac{H}{W}.$	Width W and height H can be got using a minimum exterior rectangle.
Position	$x_m = \frac{1}{N_C} \sum_{i=1}^{N_C} x_i,$ $y_m = \frac{1}{N_C} \sum_{i=1}^{N_C} y_i$	(x_m, y_m) is the center of mass.

(a)   (b)   (c)
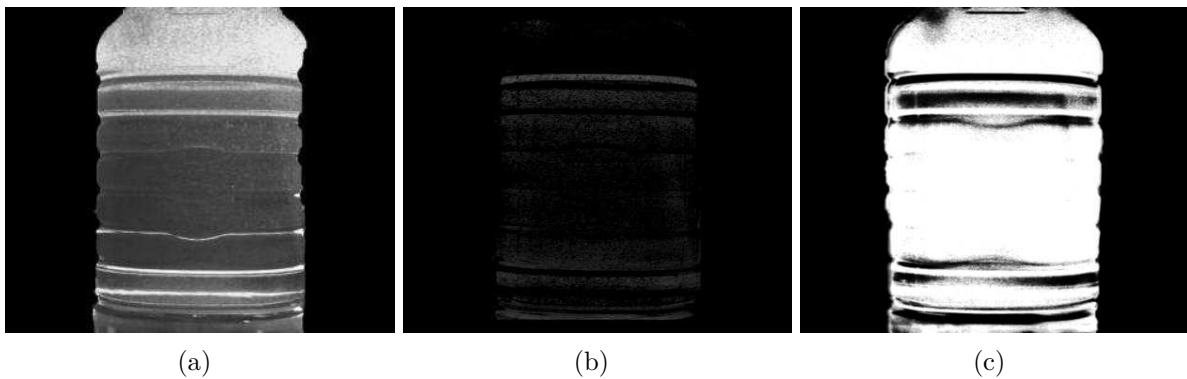
FIGURE 7. Images after applied with (a) pre-processing, (b) adaptive image variation detection and (c) structure related occurrence probability model

in Figure 7(b). Considering width of the inhomogeneous structures, the size of window is set as $121*121$. After that, we use threshold segmentation to get structural information and learn an occurrence probability image with these samples. As shown in Figure 7(c), it is obvious that inhomogeneous structures parts have the smaller possibility of foreign substances occurrence.

When the inspector detects foreign substances online, it first pre-processes the captured image. Then adaptive image variation detection is applied to locating the potential foreign substances. We set the same window size as same as above to obtain better performance for estimating the brightness disturbances caused by inhomogeneous structures. False detection caused by inhomogeneous structures is eliminated by multiplying the occurrence probability image with the difference image obtained by the adaptive image variation detection. Candidate objects are segmented by threshold of 30. Finally, the system chooses these samples' gray values, contrast values, shape features and position features as the input vectors of the SVM classifier. After training and classifying of the classifier, foreign substances identification can be realized. The final detection results are shown in Table 2.

The inspector presented in this paper has been tested in the real production line. The detection time cost is about 120ms per bottle, which is much faster than manual inspection. For comparison, we also tried the time averaging detection method after our pre-processing step, which is the most widely used background subtraction method in industry [14]. The statistic data of these two methods' detection results is shown in Table 3. It could be found out that our method performs better than time average method with higher accuracy.

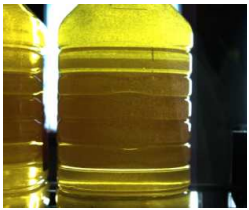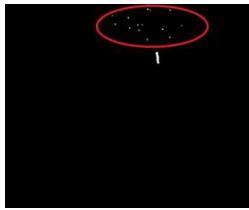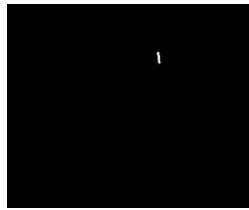TABLE 2. Foreign substances identification based on SVM
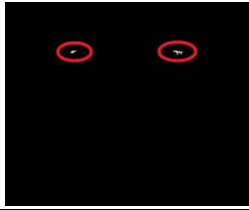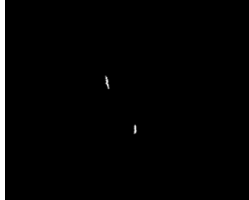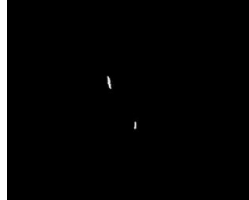
Interference type	Original image	Candidate objects	Foreign substances
bubbles			
irregular structures			
no interference			

TABLE 3. The statistic data of detection results

	Test sample numbers	False alarm rate	Missing alarm rate	Detection rate
Time average method	1000	7.2%	1.2%	91.6%
Our method	1000	0.6%	0	99.4%

6. **Conclusions.** We introduced an effective inspector for foreign substances in edible oil bottles with inhomogeneous structures based on machine vision in this paper. An adaptive image variation detection method is constructed to find out the possible foreign substances using single frame. An occurrence probability image which models the probability of each changed pixel to be true foreign substance is constructed to eliminate false detection caused by inhomogeneous structures. Comprehensive experiments showed that this inspector system has good robustness, high efficiency, and can meet real-time practical demands. In the future, we will try to use this method for detection of foreign substances at the bottom of the bottles. It is more challenging because the variation of the background is greater due to the uneven structures at the bottom.

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